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AN ALTERNATIVE APPROACH TO MONITORING FISH AND FISH HABITAT IN THE INLAND NORTHWEST

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AN ALTERNATIVE APPROACH TO MONITORING FISH AND FISH HABITAT IN THE INLAND NORTHWEST.

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EXECUTIVE SUMMARY

The development of efficient and effective monitoring protocols will depend, in part, upon successfully incorporating multiple research and management goals across several disciplines. Decision analysis has these abilities and can be used to examine the potential effects of alternative management activities, identify candidate monitoring-variables, and estimate the value of monitoring or conducting additional studies. I demonstrate the utility of decision analysis for monitoring and adaptive (i.e., experimental) management with an example of a timber harvest decision. Example models were generated using previously reported relationships and Monte Carlo simulation and the value of sampling (e.g., monitoring) was estimated via Baye's Rule. I conclude that that decision analysis can be a powerful tool for developing a future effectiveness monitoring protocols and should be considered by natural resource managers prior to adopting a monitoring strategy.

Introduction

The most important factor to consider while designing a monitoring protocol is its explicit goal(s). These are used to frame the inference space and, hence, limit the appropriate types of sampling designs and methods. For example, if the goal of a study was to estimate bull trout abundance in a specific stream, a potential survey design could include sampling fish in randomly selected reaches within that stream. This would provide an estimate of average trout density for the entire stream. However, if the goal were to estimate bull trout distribution (i.e., presence), the study would likely include a systematic sampling design to ensure more even coverage (longitudinal) of the stream. Quite often researchers neglect to give sufficient consideration to the specific goal(s) of their project or attempt to address too many, possibly conflicting goals. This can (and often does) result in the collection of data that may not adequately address even a single goal. For example, consider a situation where the goals were to estimate bull trout abundance and distribution within a stream. Typically, fish densities are estimated with maximum-effort sampling methods, such as multiple removal (Cowx 1983; Schnute 1983) or mark and recapture (Cochlan 1981). These methods are generally manpower intensive and time consuming. Consequently, the total number of sites (i.e., reaches) that can be sampled may be low due to resource limitations (e.g., funds, manpower). To adequately determine fish distribution within a stream, a relatively large number of sites generally need to be sampled to ensure good spatial coverage (Bayley and Li 1993). Thus maximum-effort sampling methods, presumably required for precise density estimates, coupled with a large number of sites needed to ensure good spatial coverage could be cost and time prohibitive. Compromises, such as reducing effort (e.g., number of passes) to free-up resources for a few additional sites, can result in data that may not provide reasonably precise density estimates and reliable estimates of fish distribution. By identifying explicit study goals *a priori*, monitoring protocols can identify potential pitfalls during the planning and design stages of a study.

For effectiveness monitoring, goals are best defined as unambiguous testable hypotheses based on the anticipated effects of the management action (Lee and Bradshaw, draft manuscript). For example, if cattle are excluded from grazing in riparian areas to increase bank stability, a potential monitoring hypothesis is that the proportion of stable banks would increase following cattle exclusion. This provides a definable benchmark with which to judge the success or failure of a management action and can facilitate response variable choice. Management actions however, can have multiple impacts. For example, timber harvest can increase peak streamflows, increasing the mortality of young fishes (Scrivener and Anderson 1984), and can also increase streambed sediment, decreasing salmonid spawning success (Scrivener and Brownlee 1989). Consequently, managers often have several possible response variables to measure, the choice of which is critical to the success or failure of the monitoring effort. Measuring variables that are insensitive to monitoring actions can impede the ability to detect change, wasting valuable resources. Similarly, some variables may require extensive sampling effort and/or may cost significantly more than other variables to collect. In order to design effective, cost efficient monitoring protocols, managers need tools for assessing the relative sensitivity of potential response variables to management actions and for estimating the value of collecting monitoring information before implementation.

Previous studies have used decision analysis to examine the sensitivity of natural resources to alternative management actions (e.g., DeNardo et al. 1989) and to estimate the value of collecting additional information (e.g., Howard et al. 1972). Decision analysis is the use of explicit, quantitative methods to examine the influences of various sources of uncertainty on (management) decisions (Clemen 1996). It allows natural resource managers to examine the expected effects of different management strategies, determine the relative influence of various sources of uncertainty (e.g., variability), and estimate the value of collecting additional data (e.g., monitoring, watershed analysis). Additional advantages of using a decision analysis include the ability to incorporate empirical models, meta-analyses, and subjective probabilities from experts into a single model, integrate information from several disciplines, and incorporate multiple management objectives. Thus, decision analysis provides an ideal framework for interdisciplinary research and management teams to cooperate to create the most effective management and effectiveness monitoring strategies.

Despite its potential advantages, decision analysis has not been widely used in natural resource management, presumably because it was originally developed for use in business and manufacturing applications (Morris 1994). Therefore, most natural resource professionals have never been exposed to the concepts. In the following section, we illustrate how decision analysis can be used for monitoring by considering a simplified hypothetical land management decision. Our goal is to familiarize natural resource professionals with decision analysis concepts rather than present a rigorous model. For a thorough and intelligible treatment of decision analysis, consult Clemen (1996).

An Example: Timber Harvest

Problem statement.- Assume that a land management team has to decide on a timber sale in a small watershed containing a population of a threatened fish species. The team economist would like to sell a large portion of the available timber to maximize profits. The biologist however, is concerned that excessive fine sediments in the streambed, resulting from a large timber harvest, might adversely affect the fish population. Furthermore, the biologist contends that excessive fine sediment could negatively impact other aquatic organisms. The soil scientist argues that sediment yield is influenced not only by the area harvested, but also by the erodability of the soils and the slope of the watershed. Of these, the soils in the watershed are thought to be moderately erodable, but the watershed slope is unknown. The hydrologist contends that both sediment yield and transport influence the amount of fine sediments in the streambed, but that the precise relationship is difficult to predict. Clearly, the team has a lot to consider before making a decision on the timber sale.

Goals.- The first step in a decision analysis is to identify the decision situation and its fundamental goals. For our example, the decision situation is whether or not to harvest timber in the small watershed. The goals of the team were articulated by the economist, who wanted to maximize profit from the timber sale, and the biologist, who wanted to maintain the threatened fish population and stream habitat that could support other aquatic organisms.

Alternatives.- The next step is to identify or formulate possible alternatives for the decisions. In some instances, the alternatives will be limited by the decision situation (e.g., simple yes/no decisions), whereas others may be varied and complicated (e.g., decisions on where and how to construct roads). Often, novel alternatives can be developed if the decision-makers are willing to allow for some creativity. For example, new timber transportation techniques may be developed as an alternative to road construction. This built-in flexibility is one of the advantages of using decision analysis because it can lead to novel solutions and important advances in resource management. For our timber harvest example, the team decides on three timber harvest alternatives: None– do not harvest any timber; Small– harvest timber from a small plot approximately 50-150 acres; Large– harvest timber from a large plot approximately 151-300 acres.

Modeling.- The next step, modeling, is perhaps the most difficult. During this process, the problem is broken down into smaller more manageable components and relationships among the components are determined. The decision model should be as simple as possible (i.e., have the fewest components) to facilitate analyses and interpretation, but should retain all of the components that will significantly affect the outcome of the decision (i.e., the model should be *requisite*, Phillips 1984). The relationships among the various components are modeled as conditional probabilities. For example, given that timber harvest area is *large*, P_L is the probability that sediment yield is low. Therefore, the states for each component must be mutually exclusive (i.e., independent of one another) and collectively exhaustive (i.e. the probabilities must add up to 1). For the timber harvest decision, the team broke the problem down into 8 components (Table 11) based, in part, on the arguments presented earlier. These included: timber harvest decision with 3 states– *none*, *small*, and *large*; sediment yield, watershed slope, streambed fine sediment, and egg-to-fry survival with 3 states each– *low*, *moderate*, and *high*; current fish population size with 3 states– *small*, *medium*, and *large*; population response with 3 states– *decreasing*, *stable*, and *increasing*; and net utility– a continuous variable representing the value of potential outcomes.

The relationships among decision components can be graphically represented in influence diagrams or alternatively, decision trees. Influence diagrams provide explicit representations of the individual components of the decision and their probabilistic dependencies. For example, the hypothetical timber harvest decision is shown in Figure 16. Geometrical shapes referred to as nodes represent individual components. Decision nodes are represented by rectangles; chance or uncertainty nodes, by ovals; and consequence nodes, by rectangles with rounded corners. A directed arc is used to indicate dependencies between model components. For example, both timber harvest and watershed slope influence sediment yield (Figure 16). Although they resemble flowcharts, influence diagrams are fundamentally different. An influence diagram represents an instantaneous moment in time. Therefore, the arcs usually (see value of information, below) do not represent the timing or sequence of events.

Decision trees are generally used to display the decision in greater detail. Similar to influence diagrams, geometric shapes are used to represent the various components of the model (Figure 17). The branches leading out of the geometric shapes represent the possible decisions, outcomes, or the chance events. For example, timber harvest has 3 branches corresponding to the decisions *none*, *small*, and *large* timber harvest area. The consequence of each choice or chance event is also displayed at the ends of the branches. For example, when streambed fines are low the probability of *low*, *moderate*, and *high* fry to egg survival are 0, 0.23, and 0.77, respectively (Figure 17). Decision trees, however, tend get very large with the addition of model components. Consequently, they are often shown in collapsed formats as shown in Figure 17.

Parameterization.- The next step during modeling is parameterizing the conditional dependencies. As discussed earlier, these can be estimated using empirical models, meta-analyses, and subjective probabilities from experts. For example, the soil scientist could use the empirical sediment yield models from Potyondy et al. (1991) to generate the probabilities for sediment yield via Monte Carlo simulation (Law and Kelton 1991). Similarly, the biologist could use the results of various published studies (e.g., Shelton and Pollock 1966, Reiser 1988, Scrivener and Brownlee 1989) to estimate the conditional probabilities for egg-to-fry survival via meta-analysis (Hunter 1982) and incorporate these into a stochastic population dynamics model to estimate fish population response. If the hydrologist did not have empirical models or published studies with which to generate estimates for streambed fines, estimates could be obtained by querying hydrologists for their expert opinion (e.g., Henrion et al. 1991). Finally, the economist, in cooperation with environmental and social scientists, could develop the net utility values by estimating the profits from timber sales and by surveying the public to determine the relative value of the natural resources (Gray 1993) and hence, the costs of environmental degradation. For our example, we used the contrived conditional probabilities and utility values listed in Tables 12 and 13, respectively. Note that these values were generated to demonstrate the decision analysis approach and are only provided as an example. Therefore, they should not be used in actual applications.

Sensitivity Analysis.- The next step is to examine the existing model with sensitivity analysis. In general, sensitivity analysis is used to identify the components that are most critical to the decision and is most useful for prioritizing additional modeling and data collection efforts (e.g., monitoring). Although there are several variations to sensitivity analysis (e.g., event and joint sensitivity analyses, Clemen 1996), the basic objective is to examine each model component and determine its relative influence on the outcome (e.g., the fish population response) or the expected value of the decision (see below). The most influential components are considered critical to the decision and hence, are given higher priority as potential monitoring variables. For example, a deterministic sensitivity analysis of the timber harvest model indicated that net utility (i.e., our measure of value) was most sensitive to egg-to-fry survival and sediment yield (Figure 18a). If collecting additional data could reduce the uncertainty (e.g., variance) in these components, monitoring efforts would be most productive by focusing on these variables. For example, a monitoring protocol could be designed to examine the influence of stream sediment and, possibly, other factors on egg-to-fry survival via an experimental (i.e., adaptive) management approach. The resultant monitoring data could then be used to update the prior egg-to-fry survival model to produce improved management decisions. However, the value (e.g., relative cost) and usefulness (i.e., reduction of uncertainty) of collecting such data should be evaluated prior to incorporating these variables into a monitoring program.

Expected Value.- Before examining the techniques for estimating the value of collecting data, we must first introduce the concepts of expected value of a decision and optimal decision-making. The expected value of a decision is simply the probability-weighted average of its possible values. For example, consider a *yes* - *no* decision with two possible outcomes, **A** and **B**, with values of 10 and 100, respectively. The conditional probabilities for **A** and **B** given a *yes* decision (e.g., P(**A** | *yes*)) are 0.75 and 0.25 and for a *no* decision, 0.5 and 0.5, respectively. Thus, the expected value of a *yes* decision would be $0.75*10 + 0.25*100 = 32.5$ and the expected value of a *no* decision, $0.5*10 + 0.5*100 = 55$. The optimal decision is simply the one with the greatest expected value, which for this example is *no*. Using a similar approach, the estimated optimal decision for the timber harvest example is *none* with an expected net utility of 33.172 (Figure 18b).

Value of Information.- A first approximation of the value of collecting additional data (e.g., watershed analysis, monitoring) can be obtained by calculating the expected value of perfect information (EVPI). EVPI is the increase in the expected value of a decision should the 'true' value of a component(s) or the relationship among components become known. Thus, it can be used, in part, to identify and rank potential variables for monitoring or additional data collection efforts. Graphically, EVPI is represented as an arc connecting an uncertainty node(s) to a decision node(s) (Figure 19). These arcs represent timing or sequence and indicate that the uncertainty will be resolved (i.e., the information will be known) before the decision is made. For example, watershed slope and current fish population size influenced two different components of the timber harvest decision (Figure 16), but were assumed to be unknown. Assuming that slope and population size could be estimated without error during a watershed analysis, the expected value of the timber harvest decision, following a watershed analysis, is estimated as the probability-weighted expected net utility for each combination of (known) watershed slope and current population size (Figure 20). In the timber harvest example, the optimal decision is *none* when watershed slope is *high* and the current population size is either *large*, *medium*, or *small* with expected values of 37.729, 36.650, and 29.335, respectively (Figure 20). Because the current population size is unknown when the decision to conduct a watershed analysis is made, the prior probabilities of a *large*, *medium*, or *small* population (i.e., 0.333) must be used to calculate the expected value. For example, the expected value of 'knowing' current population size for a watershed with a 'known' *high* slope is the sum of the probability-weighted values, i.e.,

$$(0.333 * 37.729) + (0.333 * 36.650) + (0.333 * 29.335) = 34.573.$$

Watershed slope is also unknown when the decision to conduct a watershed analysis is made. Thus, the expected value of the timber harvest decision, after a watershed analysis is completed, is the sum the probability-weighted values for each watershed slope state, 43.053 (Figure 20). EVPI is calculated as the difference between the expected value with and without a watershed analysis, 43.053 - 33.172 = 9.881. If the cost of a watershed analysis was less than the EVPI, it would increase the expected net value of the optimal decision and hence, would be beneficial to complete.

Value of imperfect information. - Although the EVPI can be useful as a first approximation, it is usually not realistic to expect sampling information to be perfect. Even the most carefully controlled experiments– or carefully made measurements– will have some uncertainty (e.g., variance) associated with them, which can affect their value. For example, 10 measurements of streambed fine sediment that lower variance 10% would be more valuable than 10 measurements that lowered variance 1%. To account for the error in measurements or models, requires the estimation of the expected value of imperfect information (EVII). EVII is considerably more complicated to estimate than EVPI. It requires an estimate of the expected outcome and the use of probabilistic rules (e.g., Baye's) to calculate probabilities and expected values. Therefore, we will outline EVII in considerable detail in the following section.

The biologist in our example has to decide whether or not to collect fish during a watershed analysis. Fish sampling efficiency (i.e., the ability to capture fish) can affect the ability to accurately estimate population size, which might reduce the value of a watershed analysis. To examine the influence of sampling efficiency on the efficacy of conducting a watershed analysis, the biologist needs to estimate EVII under different sampling efficiency scenarios. The first step in this analysis is to examine the influence of sampling efficiency on the ability to estimate fish population size in probabilistic terms. Graphically, this is depicted in an influence diagram as a dependency arc drawn from current population size to a component representing the expected sampling results (Figure 21a). Mathematically, the probability of predicting that a population is *small*, *medium*, or *large*– given the actual population size is estimated as:

$$\text{P(Predicted population size | Actual population size)} = \sum_{j=MinN}^{MaxN} \sum_{i=MinC}^{MaxC} 0.2 * \binom{j}{i} p^{i}(1-p)^{j-i} ,$$

where *MinN* and *MaxN* are the minimum and maximum number of fish for the actual population size class (e.g., *small* population: 0-5 fish[1]), *MinC* and *MaxC* are the minimum and maximum number of fish captured and p is the probability of capturing a single fish (i.e., the sampling

[1] Note that the population is assumed to be small if no fish were collected to maintain coherence (i.e., probabilities sum to 1).

efficiency). Estimates for low (20%) and high (90%) sampling efficiencies suggest that sampling efficiency significantly influences the ability to correctly estimate population size (Table 14). For example at low efficiency, the probability of estimating that a population is *medium* when the actual population is *medium* is 0.2%, whereas it is 86.7% when sampling efficiency is high. Similarly, the probability of correctly concluding that a population is large is 0.2% and 75.6% for low and high sampling efficiency, respectively (Table 14).

The second step in the analysis is to calculate the probability of estimating a particular population size (i.e., the fish sampling results), given the actual fish population size and sampling efficiency. Graphically, this is simply a matter of reversing the direction of the dependency arc from current population size to sampling results (Figure 21b). To obtain probability estimates for sampling results, requires the use of total probability. For example, the probability of estimating that a population is *small*– given low sampling efficiency is:

P(Results = *small*)

= P(Results = *small* | Actual = '*small*')*P('*small*') + P(*small* | '*medium*') *P('*medium*') +

P(*small* | '*large*') *P('*large*')

= (1.00*0.333) + (0.998*0.333) + (0.966*0.333) = 0.988.

Estimates for low and high sampling efficiencies indicate that sampling efficiency significantly influences the fish sampling results (Table 14). For example, when sampling efficiency is low, there is a 98.8% chance of concluding a population is *small*, whereas the probability is 37.8% when sampling efficiency is high.

The remaining calculations for EVII are identical to the EVPI calculations except that the sampling result probabilities (i.e., predicted population size) are used in place of the uniform priors (Table 14). Thus, the expected value of a the timber harvest decision, following fish sampling, is estimated as the probability-weighted expected net utility for estimated current population size (i.e., fish sampling results in Figures 21 and 22). Not suprisingly, the EVII for sampling low efficiency is much less, 0.067, than high sampling efficiency, 2.409 (Figure 22). In this example, the biologist would probably decide not to sample fish if the expected sampling efficiency was low. If the biologist had a choice between an expensive high-efficiency sampling method (e.g., multiple removal electrofishing) and a less expensive low-efficiency method (e.g., snorkeling), the EVII could also provide a means of estimating the net value of using each method by subtracting the method-specific sampling costs from EVII. The estimation of EVII can also be extended to any component of the decision model, so that the feasibility of additional research or monitoring efforts can be evaluated *a priori*. In the timber harvest example, the sensitivity analysis indicated that egg-to-fry survival significantly affected the expected value of the decision, making it a potential candidate for monitoring. To examine the usefulness of monitoring egg-to-fry survival, the biologist could estimate the EVII for likely outcomes of monitoring.

Conclusion

The efficient and effective management of natural resources will depend, in part, upon the development of tools that can combine research and management goals and integrate across disciplines. Decision analysis has these abilities and, as we have demonstrated, can be used to examine the potential effects of alternative management activities, identify candidate monitoring variables, estimate the value of collecting information or conducting studies, and evaluate competing decision models (hypotheses). Therefore, we believe that decision analysis can be a powerful tool for developing monitoring protocols.

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Table 1. Components of the hypothetical timber harvest decision model. The corresponding influence diagram and decision tree can be found in Figures 1 and 2, respectively. Note that the states for each component are mutually exclusive (i.e., don't overlap).

Component	Node Type	Number of States	State		
Timber Harvest	Decision node	3	None	Small 50-150 acres	Large 151-300 acres
Watershed Slope[1]	Chance node	3	Low < 20%	Moderate 21-45%	High 46-75%
Sediment Yield	Chance node	3	Low	Moderate	High
Streambed Fines	Chance node	3	Low < 20%	Moderate 21-40%	High > 41%
Egg-to-Fry Survival	Chance node	3	Low < 10%	Moderate 11-25%	High >26%
Current Fish Population Size[1]	Chance node	3	Small 1-5 adult females	Medium 6-10 adult females	Large 11-15 adult females
Population Response	Chance node	3	Decreasing	Stable	Increasing
Net Utility	Utility node	Continuous variable			

[1]Components were assumed to be unknown and were assigned uniform probabilities (i.e., 0.333)

Table 2. Conditional probability matrices for the hypothetical timber harvest decision. Note that the probabilities in each row are collectively exhaustive (i.e., add to 1).

		Sediment Yield		
Slope	Timber Harvest	Low	Moderate	High
Low	None	0.900	0.100	0.000
	Small	0.500	0.360	0.140
	Large	0.290	0.360	0.350
Moderate	None	0.900	0.100	0.000
	Small	0.310	0.510	0.180
	Large	0.060	0.300	0.640
High	None	0.900	0.100	0.000
	Small	0.160	0.590	0.250
	Large	0.000	0.280	0.720

	Streambed Fines		
Sediment Yield	Low	Moderate	High
Low	0.832	0.167	0.001
Moderate	0.276	0.623	0.101
High	0.029	0.242	0.729

	Egg-to-Fry Survival		
Streambed Fines	Low	Moderate	High
Low	0.000	0.230	0.770
Moderate	0.230	0.580	0.190
High	0.950	0.050	0.000

Table 2. continued.

Egg-to-Fry Survival	Current Population Size	Population Response		
		Increasing	Stable	Decreasing
Low	Small	0.010	0.080	0.910
	Medium	0.020	0.297	0.683
	Large	0.021	0.382	0.597
Moderate	Small	0.053	0.317	0.630
	Medium	0.067	0.645	0.288
	Large	0.091	0.694	0.215
High	Small	0.212	0.560	0.228
	Medium	0.247	0.630	0.123
	Large	0.272	0.594	0.134

Table 3. Utility values for the hypothetical timber harvest decision.

Timber Harvest	Population Response	Streambed Fines	Utility
None	Increasing	Low	82.5
		Moderate	49.5
		High	-16.5
	Stable	Low	49.5
		Moderate	16.5
		High	-49.5
	Decreasing	Low	-49.5
		Moderate	49.5
		High	-148.5
Small	Increasing	Low	132.0
		Moderate	99.0
		High	33.0
	Stable	Low	99.0
		Moderate	66.0
		High	0.0
	Decreasing	Low	0.0
		Moderate	-33.0
		High	-99.0
Large	Increasing	Low	165.0
		Moderate	132.0
		High	66.0
	Stable	Low	132.0
		Moderate	99.0
		High	33.0
	Decreasing	Low	33.0
		Moderate	0.0
		High	-66.0

Table 4. Probabilities for current and predicted fish population size and sampling results based on low (20%) and high (90%) sampling efficiencies.

Current Population Size Probabilities		
Small	Medium	Large
0.333	0.333	0.333

	Actual Population Size	Predicted Population Size: Small	Medium	Large
Low Sampling Efficiency	Small	1.000	0.000	0.000
	Medium	0.998	0.002	0.000
	Large	0.966	0.032	0.002
High Sampling Efficiency	Small	1.000	0.000	0.000
	Medium	0.133	0.867	0.000
	Large	<0.001	0.244	0.756

	Sampling Results Probabilities	
Predicted Population Size	Low Sampling Efficiency	High Sampling Efficiency
Small	0.988	0.378
Medium	0.012	0.370
Large	<0.001	0.378

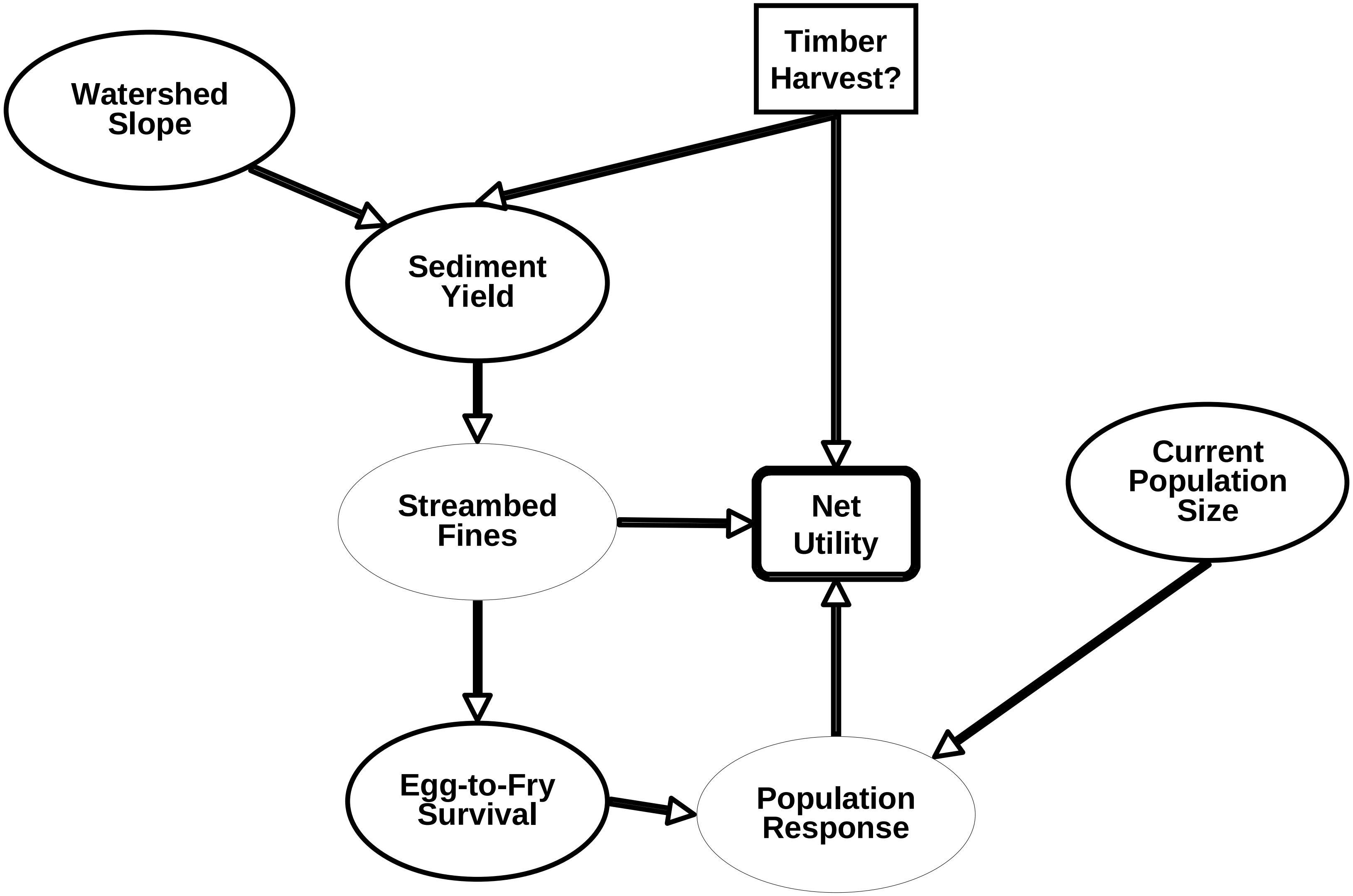


Figure 1. Influence diagram of hypothetical timber harvest decision.

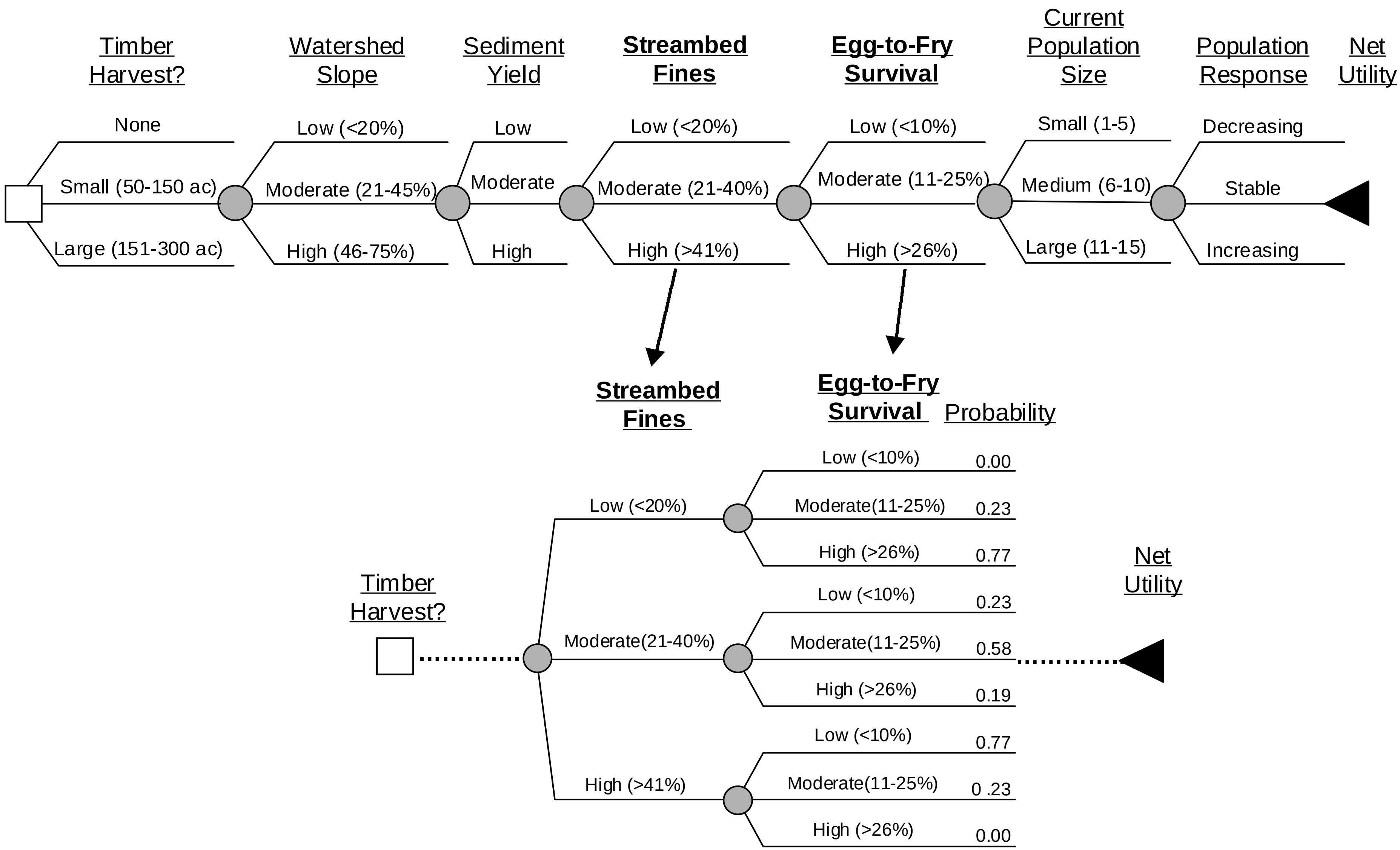


Figure 2. Incomplete tree diagram of hypothetical timber harvest decision (top) and expanded section of streambed fines and egg-to-fry survival components (bottom).

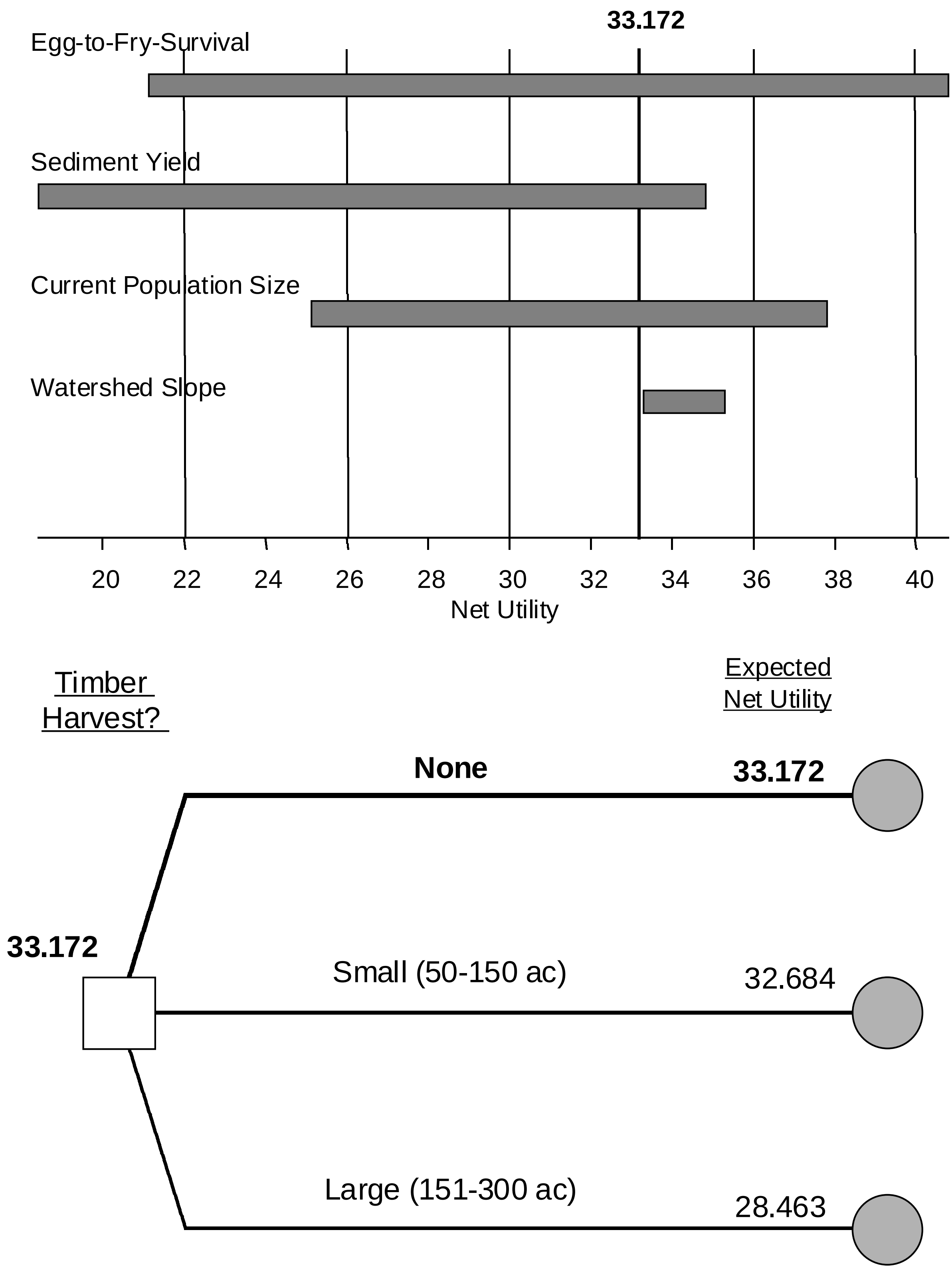


Figure 3. (a) Tornado diagram for sensitivity analysis with components listed from greatest (top) to least influential and (b) an incomplete decision tree for the hypothetical timber harvest decision displaying the optimal decision (heavy line) and expected value (bold).

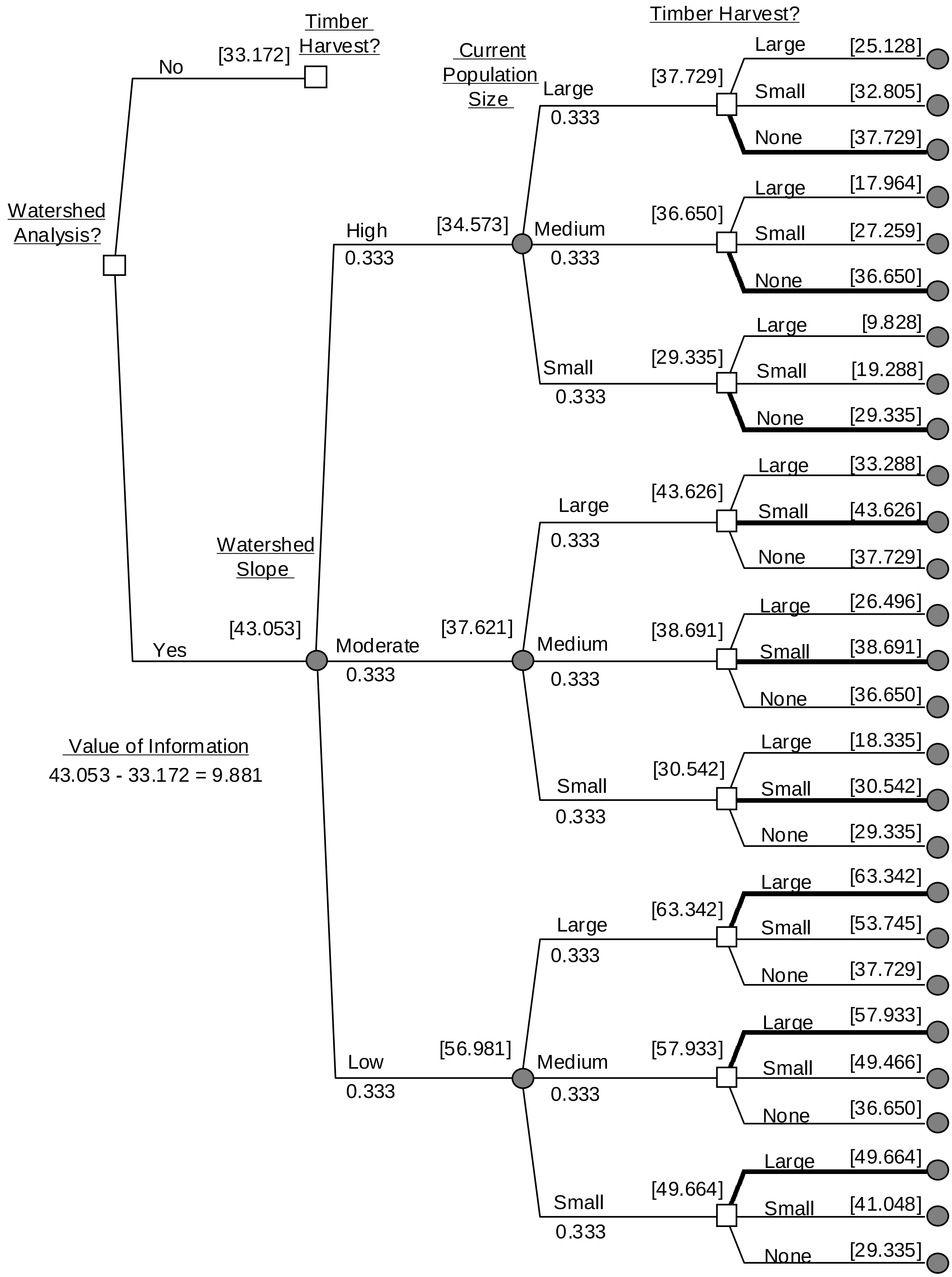


Figure 4. Incomplete decision tree for the hypothetical timber harvest decision displaying the watershed analysis perfect information alternative. Expected values are shown in brackets, probabilities are beneath the tree branches, and optimal decision pathways are shown with heavy lines.

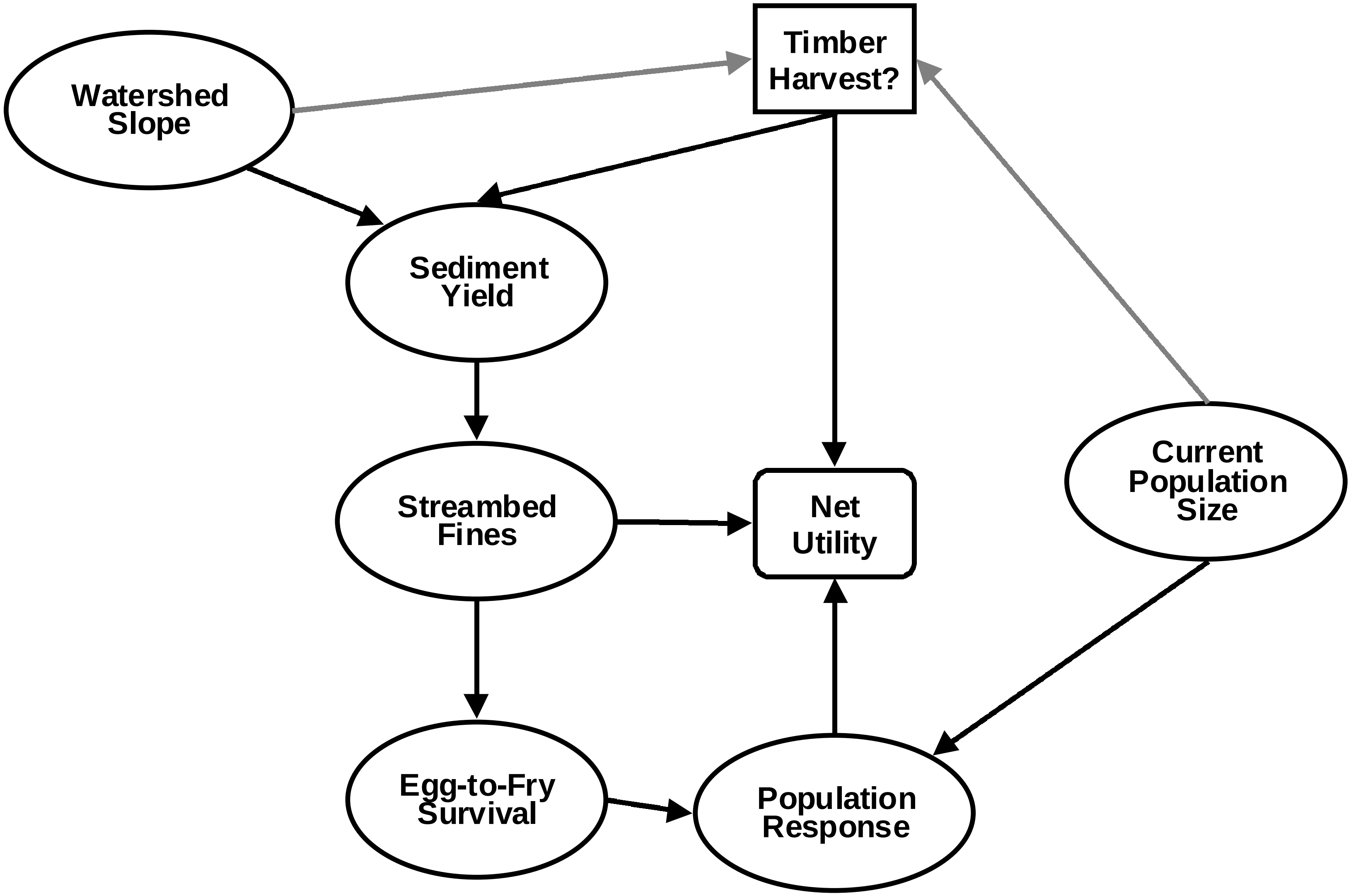
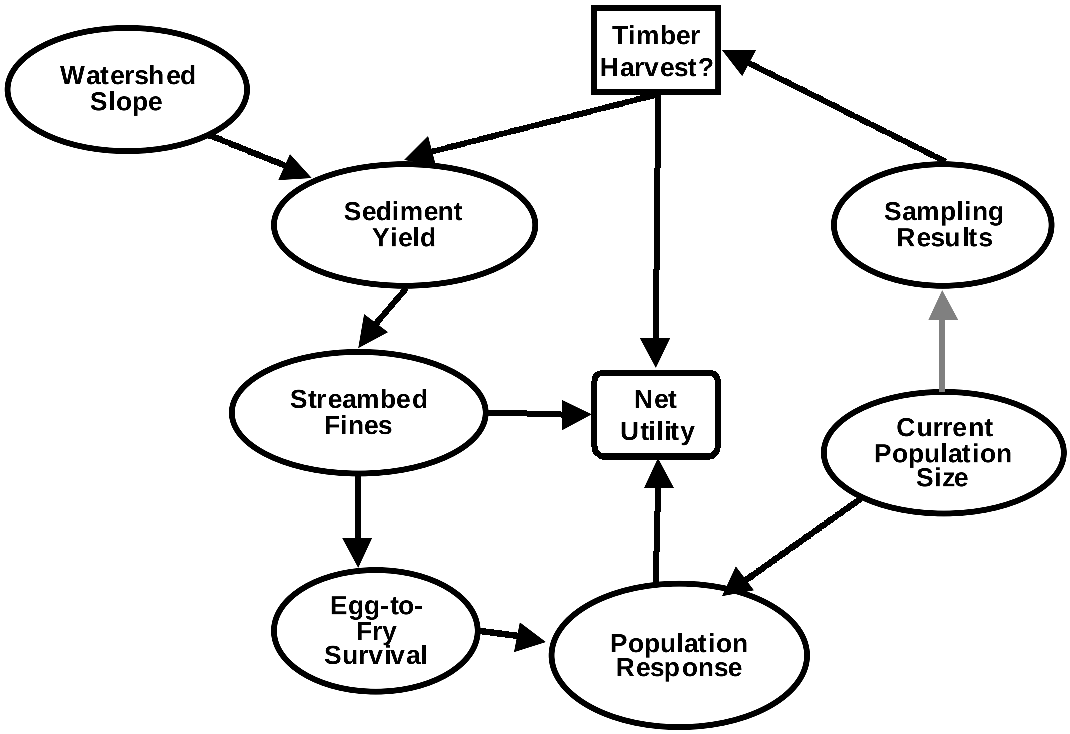


Figure 5. Influence diagram for the hypothetical timber harvest decision with perfect information for watershed slope and current population size. Grey arcs connecting watershed slope and current population size to timber harvest connote timing and indicate that this information will be known before the decision is made.

a.



b.

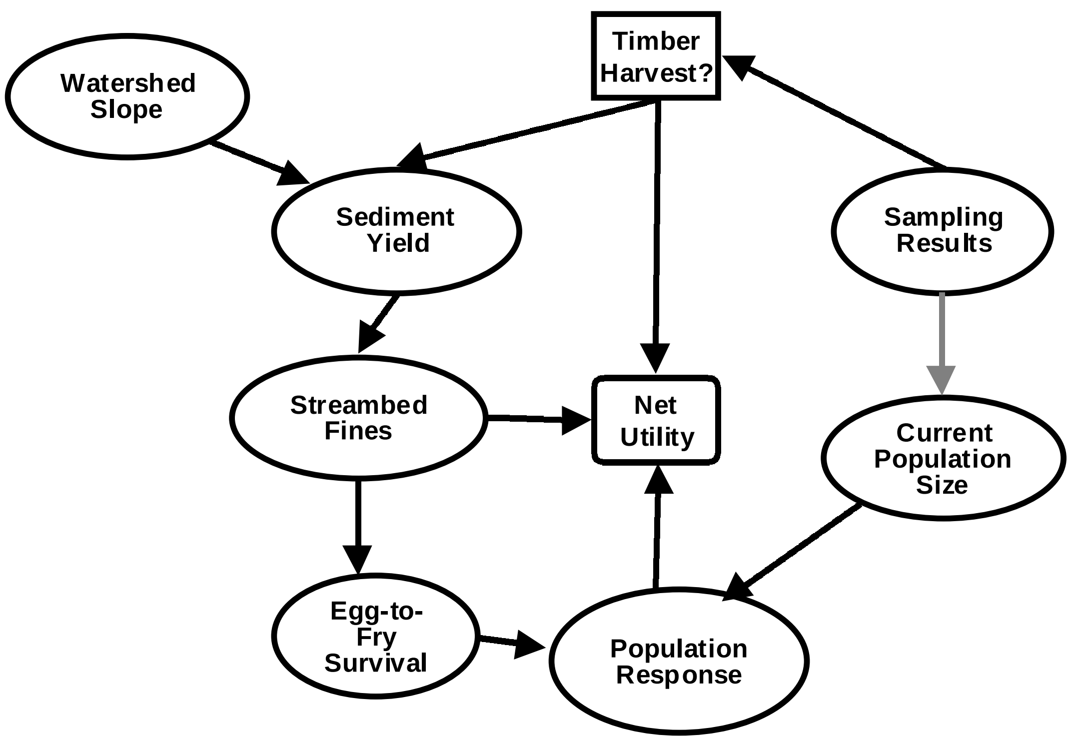


Figure 6. Influence diagram of imperfect fish sampling information with the (a) first step- conditioning sampling results on actual population size and (b) the second step- reversing the arrow between sampling results and current population size to obtain sampling results probabilities.

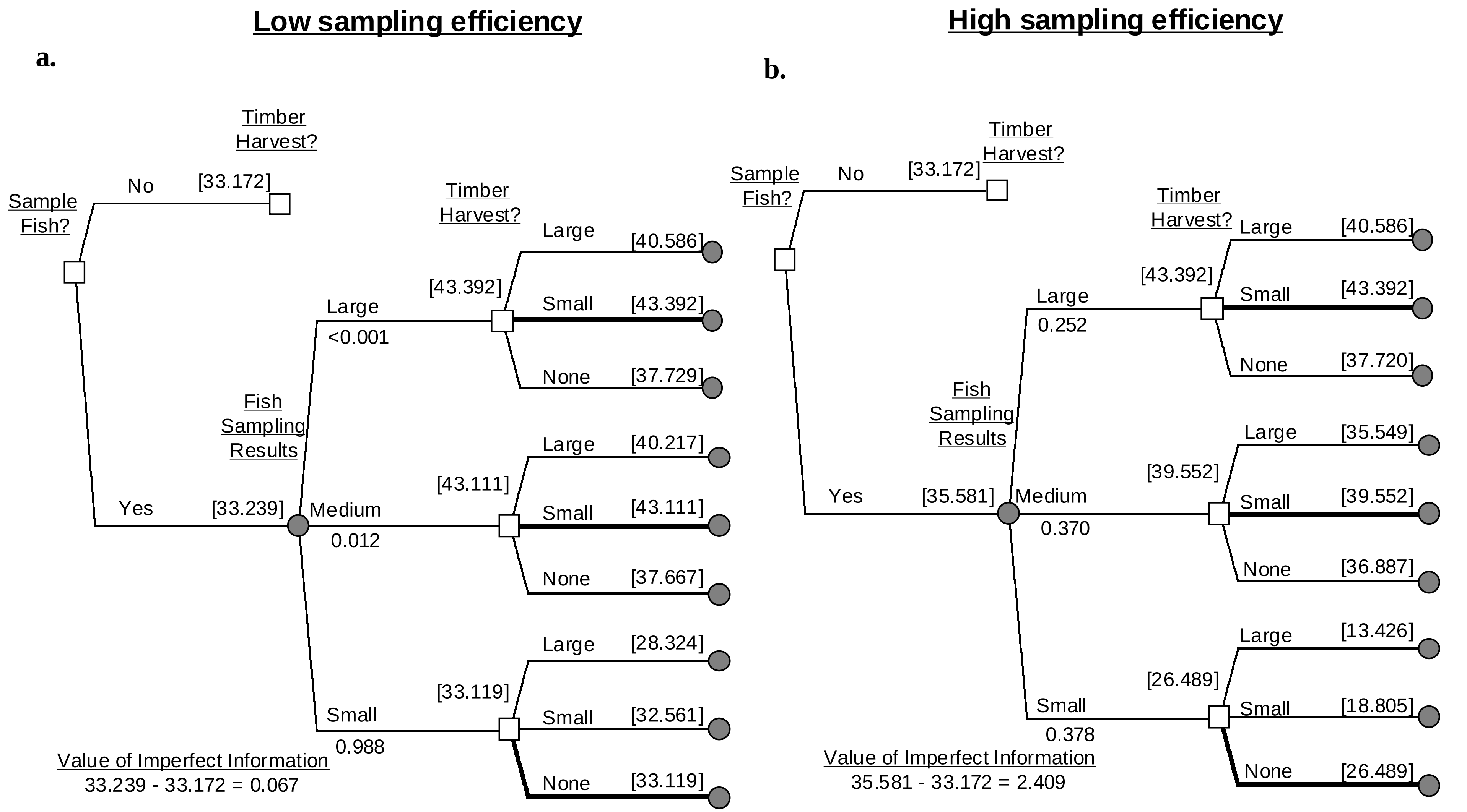


Figure 7. Incomplete decision tree for the hypothetical timber harvest decision displaying the fish sampling imperfect perfect information alternatives for (a) low (20%) and (b) high (90%) sampling efficiencies. Expected values are shown in brackets, probabilities are beneath the tree branches, and optimal decision pathways are shown with heavy lines.